Semantic Folding Theory

And its Application in Semantic Fingerprinting

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Semantic Folding Theory

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Abstract

It is common scientific practice to investigate phenomena, which cannot be explained by an existing set of theories, scientifically by applying statistical methods. This is how medical research has led to coherent treatment procedures, which provided a great deal of usefulness to patients. By observing many cases of a disease and by identifying and accounting its various cause and effect relationships, the statistical evaluation of these records allowed to make thoughtful predictions and to find adequate treatments as countermeasures. Nevertheless, since the rise of molecular biology and genetics, we can observe how medical science moves from the time-consuming trial and error strategy to a much more efficient, deterministic procedure that is grounded on solid theories and will eventually lead to a fully personalized medicine.

The science of language had a very similar development. In the beginning, extensive statistics analyses led to a good analytical understanding of the nature and the functioning of human language and culminated in the discipline of linguistics. With the increasing involvement of computer science into the field of linguistics, it turned out that the observed linguistic rules were extremely hard to use for the computational interpretation of language. In order to allow computer systems to perform language based tasks comparable to humans, a computational theory of language was needed and as no such theory was available, research turned again towards a statistical approach by creating various computational language models derived from simple word count statistics. Although there were initial successes, statistical Natural Language Processing (NLP) suffers two main flaws: The achievable precision is always lower than the one of humans and the algorithmic frameworks are chronically inefficient.

The Semantic Folding Theory (SFT) is the attempt to develop an alternative computational theory for the processing of language data. While nearly all current methods of processing natural language based on its meaning use in some form or other word statistics, Semantic Folding uses a neuroscience rooted mechanism of distributional semantics.

After capturing a given semantic universe of a reference set of documents by means of a fully unsupervised mechanism, the resulting semantic space is folded into each and every word-representation vector. These vectors are large, sparsely filled binary
Semantic Folding Theory

vectors. Every feature bit in this vector not only corresponds but also equals a specific semantic feature of the folded-in semantic space and is therefore semantically grounded. The resulting word-vectors are fully conforming to the requirements for valid word-SDRs (Sparse Distributed Representation) in the context of the Hierarchical Temporal Memory (HTM) theory by Jeff Hawkins. While the HTM theory focuses on the cortical mechanism for identifying, memorizing and predicting reoccurring sequences of SDR patterns, the Semantic Folding theory describes the encoding mechanism that converts semantic input data into a valid SDR format, directly usable by HTM networks. The main advantage of using the SDR format is that it allows any data-items to be directly compared. In fact, it turns out that by applying Boolean operators and a similarity function, many Natural Language Processing operations can be implemented in a very elegant and efficient way.

Douglas R. Hofstadter’s Analogy as the Core of Cognition is a rich source for theoretical background on mental computation by analogy. In order to allow the brain to make sense of the world by identifying and applying analogies, all input data must be presented to the neo-cortex as a representation that is suited for the application of a distance measure.

The two faculties - making analogies and making predictions based on previous experiences - seem to be essential and could even be sufficient for the emergence of human-like intelligence.
Part 1: Semantic Folding Theory and Background

Introduction

Human language is recognized as a very complex domain since decades. No computer system has been able to reach human levels of performance so far. The only known computational system capable of proper language processing is the human brain. While we gather more and more data about the brain, its fundamental computational processes still remain obscure. The lack of a sound computational brain theory also prevents the fundamental understanding of Natural Language Processing. As always when science lacks a theoretical foundation, statistical modeling is applied to accommodate as many sampled real-world data as possible.

An unsolved fundamental issue is the actual representation of language (data) within the brain, denoted as the “Representational Problem”.

Starting with Jeff Hawkins’ “Hierarchical Temporal Memory” (HTM) theory, a consistent computational theory of the human cortex, we have developed a corresponding theory of language data representation: The Semantic Folding Theory.

The process of encoding words, by using a topographic semantic space as distributional reference frame into a sparse binary representational vector is called Semantic Folding and is the central topic of this document.

Semantic Folding describes a method of converting language from its symbolic representation (text) into an explicit, semantically grounded representation that can be generically processed by Hawkins’ HTM networks. As it turned out, this change in representation, by itself, can solve many complex NLP problems by applying Boolean operators and a generic similarity function like the Euclidian Distance.
Semantic Folding Theory

Many practical problems of statistical NLP systems, like the high cost of computation, the fundamental incongruity of precision and recall\(^1\), the complex tuning procedures etc., can be elegantly overcome by applying Semantic Folding.

**Origins and Goals of the Semantic Folding Theory**

The **Semantic Folding Theory** is built on top of the **Hierarchical Temporal Memory Theory** of Jeff Hawkins\(^i\). His approach to understanding how neo-cortical information processing works, while staying closely correlated to biological data, is somewhat different from the more mainstream projects that have either a mainly *anatomic* or a mainly *functional mapping* approach.

The **neuroscientists** working on micro-anatomic models\(^ii\) have developed sophisticated techniques for following the actual 3D structure of the cortical neural mesh down to the microscopic level of dendrites, axons and their synapses. This enables the creation of a complete and exact *map of all neurons* and their interconnections in the brain. With this wiring diagram they hope to understand the brains functioning from ground up.

**Research in functional mapping**, on the other hand, has developed very advanced imaging and computational models to determine how the different patches of cortical tissue are interconnected to form functional pathways. By having a complete inventory\(^iii\) of all existing pathways and their functional descriptions, the scientists hope to unveil the general information architecture of the brain from ground up.

In contrast to these primary data-driven approaches, Jeff Hawkins’ **HTM-Theory** aims to understand and identify principles and mechanisms by which the mammalian neo-cortex operates. Every characteristic identified can then be matched against evidence from neuro-anatomical, neuro-physiological and behavioral research. A sound theory of the neo-cortex will in the end fully explain all the empirical data that has been accumulated by generations of neuroscientists to date.

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\(^{1}\) The more you get of one, the less you have of the other.
The Semantic Folding Theory tries to accommodate all constraints defined by Hawkins’ Cortical Learning principles while staying biologically plausible and explaining as many features and characteristics of human language as possible. The SFT provides a framework for describing how semantic information is handled by the neo-cortex for natural language perception and production, down to the fundamentals of semantic grounding during initial language acquisition. This is achieved by proposing a novel approach to the representational problem, namely the capacity to represent meaning in a way that it becomes computable by the cortical processing infrastructure. The possibility of processing language information at the level of its meaning will enable a better understanding of the nature of intelligence, a phenomenon closely tied to human language.

The Hierarchical Temporal Memory Model

The HTM Learning Algorithm is part of the HTM (Hierarchical Temporal Memory) model developed by Jeff Hawkins. It is not intended to give a full description of the HTM model here, but rather to distill the most important concepts in order to understand the constraints within which the Semantic Folding mechanism operates.

Online Learning From Streaming Data

From an evolutionary point of view, the mammalian neo-cortex is a recent structure that improves the command and control functions of the older (pre-mammalian) parts of the brain. Being exposed to a constant stream of sensorial input data, it continuously learns about the characteristics of its surrounding environment, building a sensory-motor model of the world that is capable of optimizing an individual’s behavior in real time, ensuring the well-being and survival of the organism. The optimization is achieved by using previously experienced and stored information to modulate and adjust the older brain’s reactive response patterns.

Hierarchy of Regions

The neo-cortex, in general, is a two-dimensional sheet covering the majority of the brain. It is composed of microcircuits with a columnar structure, repeating all over its extent. Regardless of their functional role (visual, auditory or proprioceptive), the microcircuits do not change much of their inner architecture. This micro-architecture is even stable
across species, suggesting that it is not only evolutionary older than the differentiation of the various mammalian families but also that it is **implementing a basic algorithm to be used for all (data) processing**.

Although anatomically identical, the surface of the neo-cortex is functionally subdivided into different regions. Every region receives inputs either originating from a sensorial organ or being generated by the outputs of another region. The different regions are organized in hierarchies. Every region outputs a **stable representation for each learned sequence of input patterns**, which means that the fluctuations of input patterns become continuously slower while ascending hierarchical layers.

**Sequence Memory**

Every module performs the same fundamental operations while its inputs are exposed to a continuous stream of patterns. It detects the presence of patterns that reoccur frequently and stores the sequence in which they appear. Every recognized sequence generates a distinct pattern that is exposed at the output stage of the module. During the period where the input flow is within a sequence, each module also generates a **compound pattern containing a union** of all possible patterns that could, according to its stored experience, occur in the near future, corresponding to its **prediction output**.

The above capabilities describe a **memory system** rather than a processing system as one might expect to find in this highest brain structure. This memory system is capable of processing data just by storing it. From a logical point of view, the address to a specific (virtual) memory location is provided by an input vector where every bit corresponds to a specific semantic feature originating from the sensorial stream. The address therefore consists of a very long binary vector. Contrary to a traditional computer system, this address is not explicitly set by a processor core but forms a continuous stream originating from the sensorial afferences. The data content of this (virtual) memory cell contains structured content: 1) the stable representation (in SDR form) of the current sequence 2) the union of the subsequent patterns (in SDR form) of the current sequence. Unlike traditional computer systems, where processing occurs along the “program”, the cortical processing is paced by the incoming stream of sensor data.
Computer scientists have developed a similar engineering concept, named **Content Addressable Memory (CAM)**. These CAMs have shown substantial advantages over Von Neumann architectures that use Arithmetic-Logic Units (ALU) and address pointers to perform computations. In a CAM the query is represented by a unique binary pattern. This binary representation is directly used as an address to identify and activate a specific memory cell, which contains the result data for the query representation provided. The result is always delivered within a single clock-cycle, regardless of how complex the query input was. This constant and minimal processing delay, independent of the nature of the processed data, is essential to provide an organism with useful real-time information about its surrounding.

A second big advantage of the CAM principle is that the amount of data that can be processed (in real time) increases linearly with the amount of available memory. More modules mean more processing power, which is a very effective way for evolution to adapt and improve the mammalian brain, just by augmenting the amount of cortical real estate. Contrary to nature's ability to easily grow the number of modules into astronomical figures, engineers experienced the need for massive amounts of memory to be a fundamental restriction for the whole CAM approach, which explains why today's CAMs have only very limited practical applications, far away from any general purpose computing.

**Sparse Distributed Representations**

The memory needed for a CAM can be substantially reduced if compression is applied to the addresses generated. Technical CAM implementations use **dense binary hash values** where every combination of address-bits points to a single memory location. Unfortunately, the computational effort to encode and decode the hash values is very high and counteracts - with growing memory space - the speed advantages of the CAM approach. Nevertheless, due to the smaller and constant word size (8, 16, 32, 64 ... bits), the dense representation scheme became the fundament of today's computer technology. It led, away from CAM-computing, to a continuously increasing need for **more and more powerful serial processing cores**.
Semantic Folding Theory

Fig. 1: Dense representation of the word "cat", individual bits don't carry meaning

By using a dense representation format, every combination of bits identifies a specific data item. This would be efficient in the sense that it would allow for much smaller word sizes but it would also create the need for a dictionary to keep track of all the data items recorded. The longer the dictionary list would become, the longer it would take to find and retrieve any specific item. This dictionary could link the set of stimuli corresponding to cat to the identifier 011000110110000101110100 therefore materializing the semantic grounding needed to process the data generated by the surrounding world.

Instead of realizing the semantic grounding through the indirection of a dictionary, it could also occur at the representation level directly. Every bit of the representation could correspond to an actual feature of the corresponding data item that has been perceived by one or more senses. This leads to a much longer representation in terms of number of bits but these long binary words have only very few set bits (sparse filling).

Fig. 2: Excerpt of a sparse representation of "cat" - every bit has a specific meaning

By storing only the positions of the set bits, a very high compression rate becomes possible. Furthermore, the use of a constantly growing dictionary for semantic grounding can be avoided.

By using a sparse data representation, CAM-computing becomes possible by simply increasing the number of cortical modules deployed. But one big problem remains: noise. Unlike silicon based devices, biological systems are very imprecise and unreliable,
introducing **high levels of noise** into the memory-computing process. False activation or false dropping of a single bit in a dense representation renders the whole word into something wrong or unreadable. Sparse representations are more resistant to dropped bits as not all descriptive features are needed to identify a data item correctly. But shifted bit-positions are still not tolerated as the following example shows.

![Image](image.png)

**Fig. 3: Influence of dropped and shifted bits on sparse representations**

In the above example, the various binary features are located at random positions within the sparse binary data word. A one-to-one match is necessary to compare two data-items. If we now introduce a mechanism that tries to continually group\(^2\) the feature-bits that fire simultaneously within the data word, we gain several benefits.

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\(^2\) In a spatial, topographical sense
Semantic Folding Theory

![Semantic Folding Theory Diagram](image-url)

Fig. 4: Grouping co-occurring features together improves noise resistance

A first advantage is the **substantial improvement of noise resistance** in the representation of messy real-world data. When a set bit shifts slightly to the left or the right - a blur-effect happening frequently when biological building blocks are used - **the semantic meaning of the whole data-word remains very stable**, thus contributing only a very small error value.

A second advantage is the possibility to compute a gradual similarity value, allowing a much **finer-grained semantic comparison**, which is mandatory for functions like disambiguation and inference.

*If we assume the neo-cortex to be a memory system able to process data in real-time and to be built out of repeating microcircuits, the Sparse Distributed Representation is the minimum necessary data configuration, while being the biologically most convenient data format to be used.*

**Properties of SDR Encoded Data**

I. **SDRs can efficiently be stored** by only storing the indices of the (very few) set bits. The information loss is negligible even if subsampled.

II. **Every bit in a SDR has semantic meaning** within the context of the encoding sensor.

III. **Similar things look similar**, if encoded as a SDR. Similarity can be calculated using computationally simple distance measures.

IV. **SDRs are fault tolerant** because the overall semantics of an item are maintained even if several of the set bits are discarded or shifted.

V. The **union of several SDRs** results in a SDR that still contains all the information of the constituents and behaves like a generic SDR. By comparing a new unseen SDR with a union-SDR, it can be determined if the new SDR is part of the union.
VI. SDRs can be brought to any level of sparsity in a semantically consistent fashion by using a locality based weighting scheme.

**On Language Intelligence**

A frequent assumption about intelligence is that, in a sufficiently complex circuit of artificial neurons, intelligence would emerge and manifest itself by generating behavior indistinguishable from humans.

In Jeff Hawkins’ HTM theory, however, intelligence seems to be rather a **principle of operation** than an emerging phenomenon. The learning algorithm in the HTM microcircuits is a comparably simple storage mechanism for short sequences of SDR-encoded sensor or input data. Whenever a data item is presented to the circuit, a prediction of what data items are expected next is generated. This anticipatory sensor-data permits the pre-selection and optimization of the associated response by choosing from a library of previously experienced and stored SDR-sequences. This **intelligent selection step** is carried out by applying prediction and generalization functions to the SDR memory cells.

It has been shown that, on one hand, **prediction SDRs** are generated by creating an “OR” (union) of all the stored SDRs that belong to the currently active sequence. This prediction SDR is passed down the hierarchy and used to **disambiguate unclear data** to fill up incomplete data and to strengthen the storage persistence of patterns that have been predicted correctly.

On the other hand, the **generalized SDRs** could be generated by creating an “AND” (intersection) of the stored SDRs within the current sequence. This generalized SDR is passed up the hierarchy to the next higher HTM-layer **leading to an abstraction of the input data** to detect and learn higher-level sequences or to locate similar SDR-sequences.

In fact, intelligence is not solely rooted in the algorithm used. A perfectly working HTM circuit would not exhibit intelligent behavior by itself but **only after having been exposed to sufficient amounts of relevant special case experiences**. Neo-cortical intelligence seems to be continuously saved into the HTM-system driven by input data stream while being exposed to the world.
**A Brain Model of Language**

By taking the HTM theory as a starting point, we can extend the conceptual framework by characterizing *Semantic Folding* as being an associated **data-encoding mechanism for language semantics**.

Language is a creation of the neo-cortex to exchange information between individuals. The language structures of the brain encode mental concepts into something that can be sent to the specific, language producing muscle systems. Language can be converted into acoustic signals as speech or into writing as text. There are also more exotic forms of language encoding using Morse code or Braille. But they all have something in common: **the elements of language are converted into an inner representation** that can be directly used by *comprehension circuits* where the actual processing of the language content is done.

From the semantic point of view, the smallest unit\(^3\) that contains useful, namely lexical, information consists in **words**.

**The Word-SDR Layer**

During language production, language is encoded for the appropriate communication channel like speech, text or even Morse code or Braille. After the necessary decoding steps during perception, there must be a specific location in the neo-cortex where the inner representation of a word appears for the first time.

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\(^3\) From a more formal lexical semantic point of view, the morpheme is the smallest unit encapsulating meaning. Nevertheless, the breaking down of words in morphemes seems to occur only after a sufficient number of word occurrences has been assimilated and probably occurs only at a later stage during language acquisition. Words would therefore be the *algorithm-generic* semantic atoms.
Semantic Folding Theory

The brain decodes language by converting the symbolic content of phoneme-sequences or text strings into a *semantically grounded neural representation of the meaning(s)* of a word, the "*semantic atom". These encoding and decoding capabilities are independent from the actual semantic processing. Humans are capable of learning to use new communication channels such as Braille or Morse, and can even be trained to use non-biological actuators like buttons or keyboards operated by fingers, lips, tongue or any other cortically controlled effector.

There is a place in the neo-cortex where the neurological representation of a word meaning, appears for the first time by whatever way it has been communicated. According to the HTM theory, *the word representation has to be in the SDR format*, as all data in the neo-cortex has this format. The word-SDRs all appear as output of a specific hierarchical word-SDR layer. The word-SDR layer is the first step in the hierarchy of semantic processing within the neo-cortex and could be regarded as *the language semantics receptive region*.

**Fig. 5: The word-SDR Hypothesis**
Language is regarded as an inherently human capacity. No other mammal\(^4\) is capable of achieving an information density comparable to the one of human communication, which suggests that the structure of the human neo-cortex is different, in that aspect, from other mammals. Furthermore, all humans (except for rare disabilities) have the innate capability for language and all languages have very common structures. Therefore, language capacity has to be deeply and structurally rooted in the human neo-cortical layout.

*Hypothesis: All humans have a language receptive region characterized as *word-SDR layer*.*

**Mechanisms in Language Acquisition**

Although there is much discussion about the question whether language capacity is innate or learned, the externalization of language is definitely an acquired skill, as no baby has ever spoken directly after birth.

Language acquisition is typically bootstrapped via speech and is typically extended during childhood to its written form.

**The Special Case Experience (SCE)**

The neo-cortex learns exclusively by being *exposed to a stream of patterns* coming in from the senses. Initially, a baby is exposed to repeated basic phonetic sequences corresponding to words. The mother’s repeated phonetic sequences are presented as *utterances* with increasing complexity with new words being constantly introduced.

According to the HTM-theory, the neo-cortex detects reoccurring patterns (word-SDRs) and stores the sequences where they appear. Every word-sequence that is perceived within a short time unit corresponds to a *Special Case Experience (SCE)*, comparable to perceiving a visual scene. In the same way that every perceived visual scene corresponds to a *special case experience* of a set of reoccurring shapes, colors and contrasts, every utterance corresponds to an SCE, corresponding to a specific word-sequence. In the case of visual scene perception, the same objects never produce an

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\(^4\) Only mammals have a neo-cortex.
Semantic Folding Theory

exact same retina pattern twice. In comparison, the same concepts can be expressed by language in a very large number of concrete word combinations that never seem to repeat in their exact manner.

**These SCE utterances are the only source of semantic building blocks during language acquisition.**

**Mechanisms in Semantic Grounding**

The process of binding a symbol, like a written or spoken word, to a conceivable meaning represents the fundamental semantic grounding of language.

If we assume that all patterns that ascend the cortical hierarchy are originally coming from the sensorial inputs, we can hypothesize that the meaning of a word is grounded in the sensorial afferences at the very moment of the appearance of the word-SDR at the word-SDR layer. Whenever a specific word is perceived as an SCE, **a snapshot of some (or all) of the sensorial afferences** is made and tied to the corresponding word-SDR. Every subsequent appearance of the same word-SDR generates a new\(^5\) sensorial snapshot (state) that is AND-ed with the currently stored one. Over time, only the bits that are in common within all states remain active and are therefore characterizing the semantic grounding of that word.

The mechanism described above is suitable for bootstrapping the semantic grounding process during the initial language acquisition phase. Over time, the vocabulary acquisition is not only realized using sensory afferences but also based on known words that have been learned previously. Initially, semantic grounding through sensory states is predominant until a basic set of concepts is successfully processed; then the definition of words using known words increases and becomes the main method for assimilating new words.

\(^5\) The subsequent word-SDR snapshots are new in the sense that they have small differences to the previously stored one and they are the same in that they have a large overlap with the previously stored one.
Semantic Folding Theory

Definition of Words by Context
The mechanism of sensory semantic grounding seems to be specific to the developing neo-cortex as the mature brain depends mostly on existing words to define new ones. The *sensorial-state semantic grounding* hypothesis could even be extended by correlating the sensorial-grounding phase with the neo-cortex before its pruning period, which explains why it is so hard for adults to specify how the generic semantic grounding could have happened during their early childhood.

The mature way of linking a concept to a specific word is by using other, known words. Applying the previously introduced concept of a *Special Case Experience* the mechanism could be described as follows: a sequence of words received by the sensory system within a sufficiently short perceptive time-interval could be regarded as an instance of a *Linguistic Special Case Experience*, corresponding to a statement, consisting of one or more sentences. In the case of written language, this Linguistic Special Case Experience would be a **text snippet representing a context**. This text snippet can be regarded as a context for every word that is contained in it. Eventually, **every word will get linked to more and more new contexts**, strengthening its conceptual grounding. The linking occurs by ORing the new Special Case Experience with the existing ones, thereby increasing the number of contexts for each word.

Semantic Mapping
As described earlier, **every word is characterized by its list of contexts in which it appears**. A context being itself the list of terms encountered in a previously stored SCE (utterance or text snippet).

![Fig. 6: Creation of a simple 1D-word-vector](image-url)
Semantic Folding Theory

This one-dimensional vector could be directly used to represent every word. But to unlock the advantages of Semantic Folding, a second mapping step is introduced that not only captures the co-occurrence information but also the semantic relations among contexts to enable understanding through the similarity of distributions.

The contexts themselves represent vectors that can be used to create a two-dimensional map in such a way that similar context-vectors are placed closer to each other than dissimilar ones, using topological (local) inhibition mechanisms and/or by using competitive Hebbian learning principles.

![Distribution of the contexts on the semantic 2D map](image)

This results in a 2D-map that associates a coordinate pair to every context in the repository of contexts (the sum of all perceived SCEs). This mapping process can be maintained dynamically, always positioning a newly perceived SCE onto the map, even capable of growing the map on its borders if new words or new concepts appear.

*Every perceived SCE strengthens, adjusts or extends the existing semantic map.*
Semantic Folding Theory

This map is then used to encode every single word by associating a binary vector containing a “1” to each word, if the word is contained in the context at a specific position and a “0” if not.

![Encoding of a word as word-SDR](image)

After serialization, we have a binary vector that has a natural SDR format:

- A word typically appears only in a very small number of the stored contexts. The vector is therefore sparse.
- Although the vector is used in its serialized notation, the neighboring relationships between the different positions are still governed by the 2D topology, corresponding to a topological 2D-distribution.
- If a set bit shifts its position (up, down, left or right), it will misleadingly represent a different adjacent context. But as adjacent contexts have a very similar meaning due to the folded-in map, the error will be negligible or even unnoticeable representing a high noise resistance.
- Words with similar meanings look similar due to the topological arrangement of the individual bit-positions.
- The serialized word-SDRs can be efficiently compressed by only storing the indices of the set bits.
- The serialized word-SDRs can be subsampled to a high degree without losing significant semantic information.
- Several serialized word-SDRs can be aggregated using a bitwise OR function without losing any information brought in by any of the union’s members.
Metric Word Space

The set of all possible word-SDRs corresponds to a **word-vector-space**. By applying a distance metric (like the Euclidian distance) that represents the semantic closeness of two words, the word-SDR space satisfies the requirements of a metric space:

- Distances between words are always non-negative.
- If the distance between two words is 0 then the two words are identical (perfect synonyms).
- If two words \( A \) and \( B \) are in a distance \( d \) from each other, \( d(A,B) = d(B,A) \). (Symmetry).
- For three distinct words \( A, B, C \) we have \( d(A,C) \leq d(A,B) + d(B,C) \). (Triangle inequality).

By considering the word-SDR space as a metric space, we can revert to a rich research corpus of mathematical properties, characteristics and tools that find their correspondence in the metric space representation of natural language.

Similarity

**Similarity is the most fundamental operation performed in the metric word-SDR-space.** Similarity should not be directly interpreted as word synonymy, as this only represents a special case of semantic closeness that assumes a specific type of distance measure, feature selection and arrangement. Similarity should be seen as a more flexible concept that can be tuned to many different, language relevant nuances like:

- Associativity
- Generalization
- Dependency
- Synonymy
- Etc.

The actual distance measure used to calculate similarity can be varied depending on the goal of the operation.

As the word-SDR vectors are composed of binary elements, the simplest distance measure consists in calculating the **binary overlap**. Two vectors are close if the number of overlapping bits is large. But care must be taken, as very unequal word-frequencies can lead to misinterpretations. By comparing a very frequent word that has many set-
Semantic Folding Theory

bits with a rare word having a small number of set-bits, even a full overlap would only result in the small number of overlap-bits corresponding to the number of ones in the low-frequency term.

Other distance/similarity measures that could be applied:
- Euclidian distance
- Hamming distance
- Jaccard similarity
- Cosine similarity
- Levenshtein distance
- Sørensen–Dice index
- Etc.

Dimensionality in Semantic Folding

The Semantic Folding process takes symbolic word representation as input and converts it into an n-dimensional SDR-vector that is semantically grounded through the 2D materialization-step of the semantic map.

The main reason to choose a 2D-map over any other possible dimensionality primarily lies in the fact that the word-SDRs are intended to be fed into cortical processing systems that in turn try to implement cortical processing schemes, which happen to have evolved into a 2D arrangement.

In order to achieve actual materialization of the word-SDRs, the neighboring relationships of adjacent bits in the data should directly translate to the topological space of neo-cortical circuits. Without successful materialization of the word-SDRs, semantic grounding would not be possible, making inter-individual communication - the primary purpose of language - extremely unreliable, if not impossible.

To propagate the map-topology throughout the whole cortical extent, all afferences and efferences to or from a specific cortical area have to maintain their topological arrangement. These projections can be links between regions or pathways between sensory organs and the cortical receptive fields.
Semantic Folding Theory

If we consider the hypothetical word-SDR layer in the human cortex to be a receptive field for language, the similarity to all other sensorial input systems, using data in a 2D arrangement, becomes obvious:

- The organ of Corti in the cochlea is a sheet of sensorial cells, where every cell transmits a specific piece of sound information depending on where on the sheet it is positioned.
- Touch is obviously generating topological information of the 2D surface of the body skin.
- The Retina is a 2D structure where two neighboring pixels have a much higher probability of belonging to the same object than two distant ones.

Topographic projection seems to be a main neuro-anatomic principle that maintains an ordered mapping from a sensory surface to its associated cortical receptive structures. This constitutes another strong argument for using a 2D semantic map for Semantic Folding.

**Language for Cross-Brain Communication**

It seems reasonable to assume that a major reason for the development of language is the possibility for efficient communication. In the context currently discussed, communication can be described as the capability to send a representation of the current (neo-cortical) brain state to another individual who can then experience or at least infer the cortical status of the sender. In this case, the sensorial afferences of one neo-cortex could become part of the input of a second neo-cortex that might process this compound data differently than the sender, as it accesses a different local SCE repository. The receiving individual can then communicate this new, alternative output state back to the first individual, therefore making cooperation much easier. In evolutionary biology terms, this mechanism can be regarded as a way of extending the cortical area beyond the limits of single subject by extending information processing from one brain to the cortical real estate of social peers. The evolutionary advantages resulting from this extended cortical processing are the same that drove the growing of the neo-cortex in a first place: **higher computational power** or **increased intelligence**.
Semantic Folding Theory

Although every individual uses his proprietary version of a semantic map formed along his ontogenetic development, it is interesting to note that this mechanism nevertheless works efficiently. As humans who live in the same vicinity share many genetic, developmental and social parameters, the chance of their semantic maps evolving in a very similar fashion is high: they speak the same language, therefore their semantic maps have a large overlap. The farther apart two individuals are, regardless of whether this is measured by geographical, socio-cultural or environmental distance, the smaller the overlap of their maps will be, making communication harder.

By developing techniques to record and playback language, such as writing systems, it became possible to not only make brain states available over space but also over time. This created a fast way to expose the cortex of an individual to a large set of historically accumulated Special Case Experiences (brain-states), which equally led to incremental improvement of the acquired cortical ability to make useful interpretations and predictions.
Part 2: Semantic Fingerprinting

Theoretical Background

HTM Theory and Semantic Folding Theory are both based on the same conceptual foundations. They aim to apply the newest findings in theoretical neuroscience to the emerging field of Machine Intelligence.

The two technologies work together in a complementary fashion, Cortical.io’s Semantic Folding is the encoder for the incoming stream of data, and Numenta’s NuPIC (Numenta Platform for Intelligent Computing) is the intelligent backend. Cortical.io has implemented Semantic Folding as Retina API product, that allows converting text data into a cortex compatible representation - technically called Sparse Distributed Representation (SDR) - and performing similarity and Boolean computations on these SDRs.

Hierarchical Temporal Memory

The Hierarchical Temporal Memory (HTM) theory developed by Jeff Hawkins is a functional interpretation of practical findings in neuroscience research. HTM theory sees the human neo-cortex as a 2D sheet of modular, homologue microcircuits that are organized as hierarchically interconnected layers. Every layer is capable of detecting frequently occurring input patterns and learning time-based sequences thereof.

The data is fed into an HTM layer in form of Sparse Distributed Representations. SDRs are large binary vectors that are very sparsely filled, with every bit representing distinct semantic information.

According to the HTM theory, the human neo-cortex is not a processor but a memory system for SDR pattern sequences.

When an HTM layer is exposed to a stream of input data, it starts to generate predictions of what it thinks would be the next incoming SDR pattern based on what patterns it has seen so far. In the beginning, the predictions will, of course, differ from the actual data but a few cycles later the HTM layer will quickly converge and make more correct predictions. This prediction capability can explain many behavioral manifestations of intelligence.
Semantic Folding Theory

**Semantic Folding**

In order to apply HTM to a practical problem, it is necessary to convert the given input data into the SDR format.

What characterizes SDRs?

- SDRs are large binary vectors (several 1,000 to many millions of bits).
- SDRs have a very small fraction of their bits set to “1” at a specific point in time.
- Similar data “looks” similar when converted into SDR format.
- Every bit in the SDR has specific (accountable) meaning.
- The union of several SDRs results in an SDR that still contains all the information of its constituent SDRs.

The process of Semantic Folding encompasses the following steps:

- Definition of a reference text corpus of documents that represents the *Semantic Universe* the system is supposed to work in. The system will know all vocabulary and its practical use as it occurs in this Language Definition Corpus (LDC).
- Every document from the LDC is cut into text snippets with each snippet representing a single context.
- The reference collection snippets are distributed over a 2D matrix (e.g. 128x128 bits) in a way that snippets with similar topics (that share many common words) are placed closer to each other on the map, and snippets with different topics (few common words) are placed more distant to each other on the map. That produces a 2D semantic map.
- In the next step, a list of every word contained in the reference corpus is created.
- By going down this list word by word, all the contexts a word occurs in are set to 1 in the corresponding bit-position of a 2D mapped vector. This produces a large, binary, very sparsely filled vector for each word. This vector is called the **Semantic Fingerprint** of the word. The structure of the 2D map (the Semantic Universe) is therefore “folded into” each representation of a word (Semantic Fingerprint). The list of words with their fingerprints is stored in a database that is indexed to allow for fast matching. The system that converts a given word into a fingerprint is called Retina, as it acts as a “sensorial organ for text”. The fingerprint database is called **Retina Database** (Retina DB).
The Retina Database

This database consists of actual utterances that are distributed over a 128x128 grid. At each point of the matrix we find one to several text snippets. Their constituent words represent the topic located at this position in the semantic space. The choice of implementing the semantic space as 2D structure is in analogy to the fact that the neo-cortex, like all biological sensors (e.g. the retina in the eye, the Corti organ in the ear, the touch sensors in the skin etc.), is arranged as 2 dimensional grids.

The Language Definition Corpus

By selecting Wikipedia documents to represent the language definition corpus, the resulting Retina DB will cover “General English”. If, on the contrary, a collection of documents from the PubMed archive is chosen, the resulting Retina DB will cover “Medical English”. A LDC collection of Twitter messages will lead to a “Twitterish” Retina. The same is, of course, true for other languages: The Spanish or French Wikipedia would lead to “General Spanish” or “General French” Retinas.

The size of the generated text-snippets determines the “Associativity-Bias” of the resulting Retina. If the snippets are kept very small, (1-3 sentences) the word “Socrates” is linked to Synonymous concepts like “Plato”, “Archimedes” or “Diogenes”. The bigger the text snippets are, the more the word “Socrates” is linked towards associated concepts like “Philosophy”, “truth” or “discourse”. In practice the bias is set to a level that best matches the problem domain.

Definition of a General Semantic Space

In order to achieve cross language functionality, a Retina for each of the desired languages has to be generated while keeping the topology of the underlying semantic space the same. As a result, the fingerprint for a specific concept like “Philosophy” is nearly the same in all involved languages.

Tuning the Semantic Space

By creating a specific Retina for a given domain, all word-fingerprints make better use of the available real estate of the 128x128 area, therefore improving the semantic resolution.

Tuning a Retina means selecting relevant representative training material. This content selection task can be best carried out by a domain expert, in contrast to the optimization...
Semantic Folding Theory

of abstract algorithm parameters that traditionally require the expertise of computer scientists.

**Distributed Word Representation**

The Retina engine as well as an exemplary English Wikipedia Database is available as freely callable REST API for experimentation and testing.

A web accessible sandbox can be used by pointing a browser to [http://api.cortical.io](http://api.cortical.io).

All functionalities described in this document can be interactively tested there.

A first call to:

**API: /retina endpoint.** Get information on the available Retina

will return specifics for the published Retinas.

```
[
 {  
    "retinaName": "en_associative",
    "description": "An English language retina balancing synonymous and associative similarity.",
    "numberOfTermsInRetina": 854523,
    "numberOfRows": 128,
    "numberOfColumns": 128
   }  
]
```

*Fig. 9: Calling the Retina API to get information on the Retina Database*

**Word-SDR – Sparse Distributed Word Representation**

With the Retina API it is possible to convert any given word (stored in the Retina DB) into a word-SDR. These word-SDRs constitute the **Semantic Atoms** of the system.

The word-SDR is a vector of 16,384 bits (128x128) where every bit stands for a concrete context (topic) that can be materialized as **bag of words** of the training snippets at this position.

Due to the topological arrangement of the word-SDRs, similar words like “dog” and “cat” do actually have similar word-SDRs. The similarity is measured in the degree of overlap between the two representations. The words “dog” and “truck” have by far fewer overlapping bits.
Semantic Folding Theory

**Term to Fingerprint Conversion**

At the API: `/terms` endpoint. Convert any word into its fingerprint. The word “apple” can be converted into the Semantic Fingerprint that is rendered as a list of indexes of all set bits:

```
"fingerprint": {
  "positions": [
  ]
}]
```

Fig. 10: A Semantic Fingerprint in JSON format as the Retina-API returns it

The `/terms` endpoint accepts also multi word terms like `new york` or `united nations` and is able to represent domain specific phrases like `Director of Sales and Business Development` or `please fasten your seat belts` by a unique Semantic Fingerprint. This is achieved by using the desired kind of tokenization during the Retina creation process.
Getting Context

In order to get back words for a given Semantic Fingerprint (“what does this fingerprint mean?”) the API: `/terms/similar_terms` endpoint. Finding the closest matching Fingerprint Endpoint can be called to obtain the terms having the most overlap. The terms with most overlap constitute the contextual terms for a specific Semantic Fingerprint. As terms are usually ambiguous and have different meanings in different contexts, the similar terms function returns contextual terms for all existing contexts.

![Diagram of Word Sense Disambiguation of the word “apple”](image)

Fig. 11 Word Sense Disambiguation of the word "apple"

The fingerprint representation of the word apple contains all the different meanings like computer-related meaning, fruit-related meaning or records-related meaning. If we assume the following sequence of operations:

1) get the word with the most overlap with the word apple: the word computer
2) set all bits that are shared between apple and computer to 0
3) send the resulting fingerprint again to the similar terms function and get: the word fruit
4) set all bits that are shared between the fingerprint from step 2 and fruit to 0
5) send the resulting fingerprint again to the similar terms function and get: the word records
Semantic Folding Theory

6) ... continue until no more bits are left, then we have identified all the contexts that this Retina knows for the word apple. This process can be applied to all words contained in the Retina. In fact, this form of computational disambiguation can be applied to any Semantic Fingerprint.

Using the API: /terms/context endpoint. Finding the different contexts of a term Endpoint, any term can be queried for its contexts. The most similar contextual term becomes the label for this context and the subsequent most similar terms are returned. After having identified the different contexts, the similar term list for each of them can be queried.

Text-SDR – Sparse Distributed Text Representation

The word-SDRs represent atomic units and can be aggregated to create document-SDRs (Document Fingerprints). Every constituent word is converted into its Semantic Fingerprint. All these fingerprints are then stacked and the most often represented features produce the highest bit stack.

![Aggregation of word-SDRs into a text-SDR](image.png)
Text to Fingerprint Conversion

The bit stacks of the aggregated fingerprint are now cut at a threshold that keeps the sparsity of the resulting document fingerprint at a defined level.

Fig. 13 The sparsification has an implicit disambiguation effect

The representation uniformity of word-SDRs and document-SDRs makes semantic computation easy and intuitive for documents of all sizes. Another very useful side effect is that of implicit disambiguation. As previously seen, every word has feature bits for many different context groups in its fingerprint rendering. But only the bits of the topics with the highest stacks will remain in the final document fingerprint. All other (ambiguous bits) will be eliminated during aggregation.

Fingerprints of texts can be generated using the following endpoint.

API: /text/similar_terms endpoint. Finding the closest matching Fingerprint

Based on the text-SDR mechanism, it is possible to dynamically allow the Retina to learn new, previously unseen words as they appear in texts.

Keyword Extraction

The word-SDRs also allow a very efficient mechanism to extract the semantically most important terms (or phrases) of a text. After internally generating a document-
Semantic Folding Theory

fingerprint, each fingerprint of the constituent words is compared to it. The smallest set of word-fingerprints that is needed to reconstruct the document-fingerprint represents the semantically most relevant terms of the document.

API: /text/keywords endpoint. Finding the key terms in a piece of text

Semantic Slicing

Often it is needed to slice text into topical snippets. Each snippet should have only one (main) topic. This is achieved by stepping through the text word-by-word and sensing how many feature bits change from one sentence to the next. If many bits change from one sentence-fingerprint to the next, it can be assumed that a new topic appeared and the text is cut at this position.

API: /text/slices endpoint. Cutting text into topic-snippets

Expressions – Computing with fingerprints

As all Semantic Fingerprints are homologous (they have the same size and their feature space is equal), they can be used directly in Boolean expressions. Setting and resetting selections of bits can be achieved by ADNing, ORing and SUBtracting Semantic Fingerprints with each other.

Fig. 14 Computing with word meanings

Subtracting the fingerprint of “Porsche” from the fingerprint of “jaguar” means that all the “sports car” dots are eliminated in the “jaguar” fingerprint, and that only the “big cat” dots are left. Similar but not equal would be to make an AND of the “jaguar” and the “tiger” fingerprints.
Semantic Folding Theory

ANDing “organ” and “liver” eliminates all “piano” and “church” dots (bits) initially also present in the “organ” fingerprint.

The expression endpoint at:

API: `/expressions` endpoint. Combining fingerprints using Boolean operators.

can be used to create expressions of any complexity.

**Applying Similarity as the Fundamental Operator**

Using the Semantic Fingerprint representation for a piece of text corresponds to having semantic features in a metric space. Vectors within this metric space are compared using distance measures. The Retina API offers several different measures some of which are absolute, which means that they only take a full overlap into account, others also take the topological vicinity of the features into account.

![37% overlap](image)

**Fig. 15** Similar text snippets result in similar fingerprints

There are two different semantic aspects that can be detected while comparing two Semantic Fingerprints:

- The absolute number of bits that overlap between two fingerprints describes the **semantic closeness** of the expressed concepts.
- By looking at the topological position where the overlap happens, the **shared contexts** can be explicitly determined.
5% overlap

Fig. 16 Distinct text snippets result in dissimilar fingerprints

Because they are expressed through the combination of 16K features, the semantic differences can be very subtle.

**Comparing Fingerprints**

API: `/compare` endpoint. Calculating the distance of two Fingerprints

The comparison of two Semantic Fingerprints is a purely mathematical (Boolean) operation that is independent of the Retina used to generate the fingerprints. This makes the operation very fast, as only bits are compared, but also very scalable, as every comparison constitutes an independent computation and can therefore be spread across as many threads as needed to stay in a certain timing window.

**Graphical Rendering**

API: `/image/compare` endpoint. Display the comparison of two Fingerprints

For convenience, image representation of Semantic Fingerprints can be obtained from the image endpoint, to be included in GUIs or rendered reports.

**Application Prototypes**

Based on the fundamental similarity operation, many higher-level NLP functionalities can be built. The higher-level functions in turn represent building blocks that can be included in many different business cases.
Classification of Documents

Traditionally, document classifiers are defined by providing a sufficient large number of pre-classified documents and then by training the classifier with these training documents. The difficulty of this approach is that many complex classification tasks across a larger number of classes require large amounts of correctly labeled examples. The resulting classifier quality degrades in general with the number of classes and their (semantic) closeness.

Fig. 17 Classification using Semantic Fingerprints

With Semantic Fingerprints, there is **no need to train the classifier**. The only thing needed is a **reference fingerprint** that specifies an explicit set of semantic features describing a class. This reference set or semantic class skeleton can be obtained either through direct description by enumerating a small number of generic class features and creating a Semantic Fingerprint of this list (for example the three words “mammal” + “mammals” + “mammalian”), or by formulating an expression. By computing the expression: “tiger” AND “lion” AND “panther”, a Semantic Fingerprint is created that specifies “big cat” features.

For the creation of more subtle classes the classify endpoint:
API: `/classify/create_category_filter` endpoint. Display the comparison of two Fingerprints can be used to create optimized category filters based on a couple of example documents. The creation of a filter fingerprint has close to no latency (compared to the usual classifier training process), which makes “on the fly” classification possible. The actual classification process is done by generating a text fingerprint for each document and comparing it with each category filter fingerprint. By setting the (similarity) cut-off threshold accordingly, the classification sensitivity can be set optimally for each business case. As the cutoff is specified relatively to the actual semantic closeness, it is not deteriorating the recall of the whole system.

**Content Filtering Text Streams**
Filtering text streams is also done using the fingerprint classifier described before. The main difference is that the documents do not preexist but are classified as they come in. The streaming text sources can be of any kind like Tweets, News, Chat, Facebook posts etc.

![Diagram](image-url)

*Fig. 18 Filtering the Twitter fire hose in real-time*
Since the Semantic Fingerprint comparison process is extremely efficient, the content filtering can easily keep up with high frequency sources like the Twitter fire hose in real-time, even on very moderate hardware.

**Searching Documents**

Using document similarity for enterprise search has been on the agenda of many products and solutions in the field. The widespread use of the approach has not been reached mainly because, since an adequate document (text) representation was missing, no distance measures could be developed that could keep-up with the more common statistical search models.

With the Retina engine, searching is reduced to the task of comparing the fingerprints of all stored (indexed) documents with a query fingerprint that has either been generated by an example document (“Show me other documents like this one”) or by typing in a description of what to look for (“Acts of vengeance of medieval kings”).

![Diagram of search system](image)

**Fig. 19: A similarity based configuration of a search system**

After the query fingerprint is generated, the documents are ordered by increasing distance. In contrast to traditional search engines, where a separate ranking procedure needs to be defined, the fingerprint-based search process generates an intrinsic order for the result set. Additionally, it is possible to provide **personalized results** by simply allowing the user to specify two or three documents that relate to his interests or
Semantic Folding Theory

working domain (without needing to be directly related to the actual search query). These user-selected domain documents are used to create a “user-profile-fingerprint”. Now the query is again executed and the (for example) 100 most similar documents are selected and are now sorted by increasing distance from the profile-fingerprint. Like this, two different users can cast the same search query on the same document collection and get different results depending on their topical preferences.

Real-Time Processing Option

The Retina API has been implemented as an Apache Spark module to enable its use within the Cloudera infrastructure. This makes it possible to smoothly handle large text data loads of several terabytes and potentially even petabytes. The ability to distribute fingerprint creation, comparison etc. across an arbitrarily large cluster of machines makes it possible to do real-time processing of data streams in order to immediately send a trigger, if some specific semantic constellations occur.

Document collections of any size can be classified, simplifying the application of Big Data approaches to unstructured text by orders of magnitude.

The efficiency of the Retina API combined with the workload aggregation capability of large clusters brings “index free searching” for the first time in reach of real-world datasets. By just implementing a “brute force” comparison of all document fingerprints with the query fingerprint, an index creation is not needed anymore. Most of the costs in maintenance and IT infrastructure related to large search systems originate from the creation, updating and managing operations on the index.

In an index-free search system, a new document can be findable within microseconds after having been stored.

Using the Retina API with an HTM Backend

As stated in the beginning, HTM and Semantic Folding share the same theoretical foundations. All functionality described so far is solely based on taking advantage of the conversion of text into a SDR representation.

In the following, the combination of the Retina API as text-data encoder with the HTM backend as “sequence learner” is used in a Text Anomaly Detection configuration.
Fig. 20 Text Anomaly Detection using a HTM backend

Being exposed to a stream of text-SDRs, the HTM network learns word transitions and combinations that occur in real world sources. Based on the (text) data it was exposed to, the system constantly predicts what (word) it expects next. If the word it predicted is semantically sufficiently close to the actually seen word, the transition is strengthened in the HTM. If, on the other hand, an unexpected word (having a large semantic distance) occurs, an anomaly signal is generated.

Advantages of the Retina API Approach

Simplicity
1. No Natural Language Processing skills are needed.
2. Training of the system is fully unsupervised (no human work needed).
3. Tuning of the system is purely data driven and only requires domain experts and no specialized technical staff.
4. The provided API is very simple and intuitive to utilize.
5. The technology can be easily integrated in larger systems by incorporating the API over REST or by inclusion of a plain Java library with no external dependencies for local (Cloudera/Apache Spark) deployments.

Quality
1. Rich semantic feature set of 16K features allows a fine-grained representation of concepts.
2. All semantic features are self-learned, thus reducing semantic bias in the used language model.
Semantic Folding Theory

3. The descriptive features are explicit and semantically grounded and can be inspected for the interpretation of any generated results.
4. By drastically reducing the vocabulary mismatch, far less false positive results are generated.

Speed

1. Encoding the semantics in binary form (instead of the usual floating point matrices) provides orders of magnitudes of speed improvement over traditional methods.
2. All Semantic Fingerprints have the same size, which allows for an optimal processing pipeline implementation.
3. The system semantic is pre-calculated and doesn't affect the query response time.
4. The algorithms only imply independent calculations (no corpus relative computation) and therefore easily scale to any performance needed.
5. The applied similarity algorithm can be easily implemented in hardware (FPGA & Gate Array technology) to achieve even further performance improvements. In a document search context, the specialized hardware could provide a stable query response time of <5 microseconds, independently of the size of the searched collection.

Cross-Language Ability

If aligned semantic spaces for different languages are used, the resulting fingerprints become language independent.

Fig. 21 Language independence of Semantic Fingerprints

This means that an English message-fingerprint can be directly matched with an Arabic message-fingerprint. When filtering text sources, the filter criterion can be designed in
Semantic Folding Theory

English while being directly applied to all other languages. An application can be developed using the English Retina while being deployed with a Chinese one.

**Outlook**

A Retina System can be used wherever language models are used in traditional NLP systems. Upcoming experimental work will show if using a Retina system could improve **Speech to Text, OCR or Statistical Machine Translation** systems as they all generate candidate sentences from which they have to choose the final response by taking the semantic context into account.

Another active field of research is to find out if **numeric measurements** could also be interpreted as semantic entities like words. In this case the semantic grounding is not done by folding a collection of reference texts in the representation but by using log files of historic measurements. The correlation of the measurements will follow system specific dependencies as the correlation of words follow linguistic relationships and the system represented by the semantic space will not be “language” but an actual physical system from which the sensor data has been gathered.

A third field of research is to develop a **hardware architecture** that could speed-up the process of similarity computation. For the use in very large semantic search systems holding billions of documents, the similarity computation is the bottleneck. By using a content addressable memory (CAM) mechanism, the search-by-semantic-similarity-process could reach very high velocities.
Part 3: First Experiments combining the Retina API with NuPIC

Introduction

It is an old dream of computer scientists to make the meaning of human language accessible to computer programs. However, to date, all approaches based on linguistics, statistics or probability calculus have failed to come close to the sophistication of humans in mastering the irregularities, ambiguities and combinatorial explosions typically encountered in natural language.

Considering this fact, imagine the following experimental setup:

Experimental Setup

- A Machine Learning (ML) program that has a number of binary inputs. This ML program can be trained on sequences of binary patterns by exposing them in a time series. The ML program has predictive outputs that try to anticipate what pattern to expect next, in response to a specific anterior sequence.
- A codec program that encodes an English word into a binary pattern and decodes any binary pattern into the closest possible English word. The codec has the characteristic of converting semantically close words into similar binary patterns and vice versa. The degree of similarity between two binary patterns is measured using a distance metric such as Euclidian distance.
The codec operates using a data width of 16Kbit (16384 bits) so that every English word is encoded into a **16Kbit pattern** (binary word vector).

The ML program is configured to allow patterns of 16Kbit as input as well as 16Kbit wide prediction output patterns.

The codec is linked with the ML program to form a compound system that allows for **words as input** and **words as output**.

The **encoder** part of the codec (word to pattern converter) is linked to the ML program inputs in order to be able to **feed in sequences of words**. After every word of a sequence, the ML program outputs a binary pattern corresponding to a prediction of what it expects next. The ML program grounds its predictions on the (learned) experience of sequences it had seen previously.

The **decoder** part of the codec (pattern to word converter) is linked to the prediction outputs of the ML program. In this way, a series of words can be fed into the compound system that **predicts the next expected word at its output** based on previously seen sequences.

![Diagram of input and prediction](image)

**Fig. 23**: Concrete experiment implementation

The ML program used in this experiment is the **Hierarchical Temporal Memory (HTM)** developed by Numenta. The code is publicly available under the name of **NuPIC** and actively supported by a growing community. NuPIC implements the cortical theory developed by **Jeff Hawkins** [NuPIC White Paper].

Vienna, November 2015
NuPIC is a **Pattern Sequence Learner**. This means that the initially agnostic program\(^6\) can be **trained on sequences of data patterns** and is **able to predict a next pattern** based on previously exposed sequences of patterns.

In the following experiments the data consists of **English natural language**. We use the **Cortical.io API** to **encode words into binary patterns**, which can be directly fed into the HTM Learning Algorithm (HTM LA). Being an online learning algorithm, the HTM LA learns every time it is exposed to input data. It tries to remember frequently occurring patterns and the sequences they appeared in.

After the HTM LA has read a certain number of words, it should start to predict the next word depending on the words read previously. The learning algorithm outputs a binary prediction pattern of the same size as the input pattern, which is then **decoded by the Cortical.io API back into a word**\(^7\).

The **full stop** at the end of a sentence is interpreted by the HTM LA as an **end-of-sequence** signal, which ensures that a new sequence is started for each new sentence.

\(^6\) In its initial state the algorithm does not know of any SDR or sequence thereof.

\(^7\) The Cortical.io API returns the word for the closest matching fingerprint.
Semantic Folding Theory

**Experiment 1: What does the fox eat?**

In this first experiment, the setup is used in the simplest form. A dataset of 36 sentences, each consisting of a simple statement about animals and what they eat or like, is fed in sequence into the HTM LA. A new pattern sequence is started after each full stop by signaling it to the HTM LA. Each sentence is submitted only once. The HTM LA sees a binary pattern of 16K bits for each word and does not know anything about the input, not even which language is being used.

**Dataset**

The following 36 sentences are presented to the system:

1. frog eat flies.
2. cow eat grain.
3. elephant eat leaves.
4. goat eat grass.
5. wolf eat rabbit.
6. cat likes ball.
7. elephant likes water.
8. sheep eat grass.
9. cat eat salmon.
10. wolf eat mice.
11. lion eat cow.
12. dog likes sleep.
13. coyote eat mice.
14. coyote eat rodent.
15. coyote eat rabbit.
16. wolf eat squirrel.
17. cow eat grass.
18. frog eat flies.
19. cow eat grain.
20. elephant eat leaves.
21. goat eat grass.
22. wolf eat rabbit.
23. sheep eat grass.
24. cat eat salmon.
25. wolf eat mice.
26. lion eat cow.
27. coyote eat mice.
28. elephant likes water.
29. cat likes ball.
30. coyote eat rodent.
31. coyote eat rabbit.
32. wolf eat squirrel.
33. dog likes sleep.
34. cat eat salmon.
35. cat likes ball.
36. cow eat grass.

Please note that, for reasons of simplicity, the sentences are not necessarily grammatically correct.

**Fig. 24:** Sentences presented to the HTM LA in the experiment “What does the fox eat”

**Results**

The HTM LA is a so-called Online Learning System that learns whenever it gets data as input and has no specific training mode. After each presented word (pattern), the HTM LA outputs its best guess of what it expects the next word to be. The quality of predictions rises while the 36 sentences are learned. We discard these preliminary outputs and only query the system by presenting the beginning of a 37th sentence “fox
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eat”. The final word is left out and the prediction after the word “eat” is considered to be the answer to the implicit question: "what does the fox eat?". The system outputs the word "rodent".

Discussion

The result obtained is remarkable, as it is correct in the sense that the response is actually something that could be food for some animal, and also correct in the sense that rodents are actually typical prey for foxes.

Without knowing more details, it looks as if the HTM was able to understand the meaning of the training sentences and was able to infer a plausible answer for a question about an animal that was not part of its training set. Furthermore the HTM did not pick the correct answer from a list of possible answers but actually "synthesized" a binary pattern for which the closest matching word in the Cortical.io Retina\(^8\) happens to be "rodent".

Experiment 2: “The Physicists”

The second experiment uses the same setup as in experiment 1. This time, a different set of training sentences is used. In the first case it was the goal to generate a simple inference based on a single list of examples. Now, the inference is structured in a slightly more complex fashion. The system is trained on examples of two different professions: Physicists and Singers; on what they like: Mathematics and Fans and what the profession “Actors” like: Fans.

\(^8\) This Retina has been trained on 400K Wikipedia pages. This is also the reason why it could understand (by analogy) what a fox is without ever having seen it in the training material. What it has been seeing are the words "wolf" and "coyote", which share many bits with the word "fox".
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Dataset

Physicists:
1. marie curie be physicist.
2. hans bethe be physicist.
3. peter debye be physicist.
4. otto stern be physicist.
5. pascual jordan be physicist.
6. felix bloch be physicist.
7. max planck be physicist.
8. richard feynman be physicist.
9. arnold sommerfeld be physicist.
10. enrico fermi be physicist.
11. pascual jordan be physicist.
12. felix bloch be physicist.
13. max planck be physicist.
14. richard feynman be physicist.
15. arnold sommerfeld be physicist.
16. enrico fermi be physicist.
17. pascual jordan be physicist.
18. felix bloch be physicist.
19. max planck be physicist.
20. richard feynman be physicist.
21. arnold sommerfeld be physicist.
22. enrico fermi be physicist.
23. pascual jordan be physicist.
24. felix bloch be physicist.
25. max planck be physicist.
26. richard feynman be physicist.
27. arnold sommerfeld be physicist.
28. enrico fermi be physicist.
29. pascual jordan be physicist.
30. felix bloch be physicist.

What Physicists like:
1. eugene wigner like mathematics.
2. wolfgang pauli like mathematics.
3. arnold sommerfeld like mathematics.
4. marcos reyes like mathematics.
5. karl weierstrass like mathematics.
6. hermann von helmholtz like mathematics.
7. paul dirac like mathematics.
8. max planck like mathematics.
9. richard feynman like mathematics.
10. enrico fermi like mathematics.
11. pascual jordan like mathematics.
12. felix bloch like mathematics.
13. max planck like mathematics.
14. richard feynman like mathematics.
15. arnold sommerfeld like mathematics.
16. enrico fermi like mathematics.
17. pascual jordan like mathematics.
18. felix bloch like mathematics.
19. max planck like mathematics.
20. richard feynman like mathematics.
21. arnold sommerfeld like mathematics.
22. enrico fermi like mathematics.
23. pascual jordan like mathematics.
24. felix bloch like mathematics.
25. max planck like mathematics.
26. richard feynman like mathematics.
27. arnold sommerfeld like mathematics.
28. enrico fermi like mathematics.
29. pascual jordan like mathematics.
30. felix bloch like mathematics.

What Actors like:
1. pamela anderson like fans.
2. tom hanks like fans.
3. charlize theron like fans.
4. timothy dalton like fans.
5. kevin bacon like fans.
6. elizabeth taylor like fans.
7. mel gibson like fans.
8. bruce willis like fans.
9. kate winslet like fans.
10. george clooney like fans.
11. amy adams like fans.
12. ben stuart like fans.
13. emma stone like fans.
14. matt damon like fans.
15. leo dicaprio like fans.

What Singers like:
1. jennifer lopez like fans.
2. beyonce like fans.
3. ariana grande like fans.
4. britney spears like fans.
5. camila cabello like fans.
6. lisa marie presley like fans.
7. madonna like fans.
8. madonna like fans.
9. elton john like fans.
10. marvin gaye like fans.
11. aretha franklin like fans.
12. bonnie tyler like fans.
13. elvis presley like fans.
14. johnny cash like fans.
15. linda ronstadt like fans.
16. tina turner like fans.
17. joe cocker like fans.
18. chaka khan like fans.
19. eric clapton like fans.
20. elton john like fans.
21. willie nelson like fans.
22. hank williams like fans.
23. mariah carey like fans.
24. ray charles like fans.
25. chuck berry like fans.
26. cher like fans.
27. alicia keys like fans.
28. bryan ferry like fans.
29. dusty springfield like fans.
30. donna summer like fans.
31. james taylor like fans.
32. james brown like fans.
33. carole king like fans.
34. buddy holly like fans.
35. jerry lee lewis like fans.
36. celine dion like fans.
37. dolly parton like fans.
38. otis redding like fans.
39. meat loaf like fans.
40. phil collins like fans.
41. pete townshend like fans.
42. roy orbison like fans.
43. jerry lee lewis like fans.
44. celine dion like fans.
45. alison krauss like fans.

Please note that, for reasons of simplicity, the sentences are not necessarily grammatically correct.

Fig. 25: Training sentences presented to the HTM LA in the experiment “The Physicists”

Results

The program is started using the datasets above. This is the terminal log of the running experiment:
Starting training of CLA ...

. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .
. . . . . . . . . . . . . . . . . . . . . . .

Finished training the CLA.
Querying the CLA:
eminem be => singer
eminem like => fans
niels bohr be => physicist
niels bohr like => mathematics
albert einstein be => physicist
albert einstein like => mathematics
tom cruise like => fans
angelina jolie like => fans
brad pitt like => fans
physicists like => mathematics
mathematicians like => mathematics
actors like => fans
physicists be => physicist

Fig. 26: Terminal log showing the results of "The Physicists" experiment

Discussion

After training the HTM with this small set of examples (note that the classes What Physicists like and What Singers like are only characterized by two example sentences), a set of queries based on unseen examples of Singers, Actors and Physicists is submitted. In all cases the system was able to make the correct inferences, regardless of the verb used (be, like). The last four queries suggest that the system was also able to generalize from the concrete examples of the training sentences towards the corresponding class labels like Physicists, Actors and Singers and associate to them the correct like-preferences.

For these inferences to be possible, the system has to have access to some real world information. As the HTM itself had no preemptive knowledge, the only possible source
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for bringing in this information could have been through the language elements used as training material. But the very small amount of training material clearly does not contain all that background in a descriptive or declarative form. So the only point where the relevant context could have been introduced is through the encoding step, converting the symbolic string into a binary word pattern.
Part 4: References

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